

Impact of a Gaussian filter applied to post-reconstruction PET on radiomic features in assessing tumor heterogeneity in breast cancer.

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Abstract

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Introduction: Breast cancer (BC) is a heterogeneous disease and different parameters such as expression of hormone receptors (HR), HER2, tumor grade or Ki-67 expression account for this heterogeneity. It has been reported that Radiomic features (RF) extracted from FDG PET images also reflected BC heterogeneity. However, RF are affected by various PET acquisition parameters and reconstruction or post-reconstruction processes. In that setting, we aimed to assess the impact of a Gaussian filter applied to post-reconstruction PET images for assessing BC tumor heterogeneity.

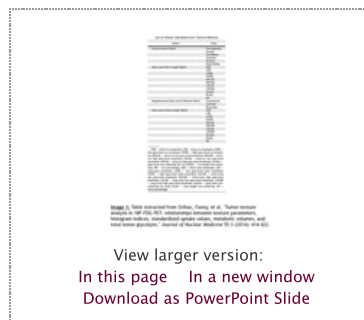
Methods: Radiomics analysis was performed in a cohort of BC patients undergoing ¹⁸F-FDGPET/CT at initial staging in our institution. PET/CT images were acquired on a GE Discovery 690 PET/CT scanner obtained 60-80 min after injection of 3.5 MBq/kg of ¹⁸F-FDG if capillary blood glucose was <11 mMol/L. A first dataset (OSEM) consisted of PET images used in routine practice obtained with OSEM reconstruction with a voxel size of 2.7 x 2.7 x 3.3 mm³. A second dataset (EANM) was analyzed for the same population, but obtained with a 7 mm Gaussian post-filter in accordance with the EARL (EANM) requirements. SUVs (max, mean, peak), 4 histogram-based features (HBI) and 31 textural indices (TI) included 6 robust TI (Homogeneity, Entropy, SRE, LRE, LGZE and HGZE) were extracted for both OSEM and EANM datasets on the same tumor volume of interest after automatic segmentation via thresholding of an initial manual delineation tumor (40% of SUVmax using LIFEx software, www.lifexsoft.org, Image 1). Pearson correlation was used to assess the relation between RF from OSEM and EANM datasets. Independent samples t-tests and ANOVA were used to compare RF as a function of BC clinical endpoints (presence of HR, HER expression and tumor grade). Similarly, we assessed the correlation between Ki-67 expression and RF on both OSEM and EANM datasets.

Results: Sixty patients with a total of 66 breast tumors were included. There were moderate to strong correlation between tumor RF from OSEM and EANM dataset (p=0.36-0.99) (Table 1). Looking at the relevance and robustness of RF to assess BC tumor texture, we found heterogeneous results. There was one significant TI SZLGE (p=0.05) extracted from OSEM dataset that could distinguish between HR- and HR+ breast tumors, whereas none were found on EANM dataset. Also, there were 6 TI significantly associated with tumor grade on OSEM dataset: LGRE (p=0.02), SRLGE (p=0.02), LRLGE (p=0.006), LZE (p=0.04), LGZE (p=0.04) and LZLGE (p=0.02) whereas 3 TI were significant on EANM dataset: Energy (p=0.05), Busyness (p=0.05) and LZLGE (p=0.04). By contrast, there were more TI significantly associated with HER2 expression on EANM dataset: 4 TI Energy (p=0.048), GLNU (p=0.03), Busyness (p=0.04), and GLNU2 (p=0.05) and only 2 TI on OSEM dataset with one similar RF, Busyness (p=0.03) and LGZE (p=0.049). Regarding Ki-67 expression, numerous moderate associations were found on both EANM and OSEM datasets, 28 TI and 27 TI respectively among which 24 similar RF including all SUVs, 2 HBI (EntropyH and KurtosisH) and numerous TI including all but one robust TI (LRE) (Table 1).

Conclusions: We found that the application of a post-reconstruction filter on PET lead to differences in breast tumor metabolic phenotype on ¹⁸F-FDG PET/CT reflected by RF calculation, though RF remained moderately to highly correlated between OSEM and EANM datasets. Some TI such as LZLGE associated with tumor grade on both OSEM and EANM seemed more robust. However, our preliminary results suggest that the use of a post-reconstruction filter as recommended EARL for multi-center SUV comparisons affect RF calculation and could lead to different results in comparison to those found in routine practice.

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Table 1 : Correlations between RF extracted from OSEM and EANM datasets using Spearman correlation t



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